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Modeling context and fuzzy personas towards an intelligent Future Internet smart home paradigm

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Abstract. It is rather true that the advent and wide proliferation of ubiquitous computing in the recent years has promoted the concept of intelligent computational social interaction as an important influencing factor of the way end-users, organizations and devices interact with each other within the new digital era. Among fields influenced is that of ''smart cities'' or the so-called ''cities of tomorrow'', where the increase and maintenance of citizens' active participation in the organization's knowledge management activities is pursued through the adoption of social computing approaches. Since cities are composed by people that inhabit them, their memories, stories, concerns and culture developing through their social interaction is of great research interest. In this paper we discuss our early efforts on designing, modeling and providing a prominent and applied knowledge modeling personalization approach, in order to achieve an ultimate goal, that of providing innovative personalized services to citizens and enhancing their everyday life within the above framework. Thus, herein we propose a novel representation way to exploit its knowledge generation and sharing capabilities in order to effectively capture and formalize corresponding knowledge information.

Keywords. knowledge management, user modeling, fuzziness, Future Internet, smart cities

Introduction

In an effort to summarize the main goal of our research work, one would agree that this paper discusses a user-centered perspective within the Internet of Things (IoT) framework. More specifically, a complete ecosystem of users within a social network is exploited and adopted within the European FP7 project ''Social&Smart'' in order to develop a so-called collective intelligence and adapt its operation through appropriately processed feedback. The ultimate aim is for the user to collectively (via the social network) and intelligently (via the adaptive network intelligence) interface, and finally control, her/his household appliances, contributing to the smart home/city paradigm. The

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central role of users is reflected on all aspects of such an ecosystem, from the family of Things that are socially governed, to the household appliances that affect our everyday life, and up to the employed hardware and software.

If we were to follow traditional user modeling researches that would have ranged from exploring reasoning approaches to different propositions towards building user models, both through establishment of meaningful user interfaces, as well as through machine learning techniques and exploration of user modeling systems. The main principle behind the notion of user modeling is the fact that having a good list of users may help us understand the functional scope of an ecosystem. For instance, questions such as ”how many different types of users will use this software/hardware?”, ”what goals will they be in pursuit of?”, ”what tasks will they need to perform?”, ”which of those tasks will the software support?”, etc. may be well answered through a well-defined user modeling scheme.

The latter stresses the fact that it is really important for user-based smart ecosystems, such as the one under examination herein, to collect and provide information about its users. Lacking information about users, such an ecosystem will not be able to adapt itself to the users' characteristics and preferences, failing to evolve and provide meaningful services. Typically, such types of required information are stored and managed in form of user models. Thus, in principle a user model represents the ecosystem's viewpoint about users. One of the fundamental questions still to be answered during the construction and content identification process of user models is *how do we go about describing users in the most semantically-relevant way?* Again, within typical use case modeling scenarios, actors are people who interact with a system; they're often described using job titles or a common name for the type of user. A user role refers, in general, to a user's responsibility when using a piece of software or participating in a business process. This relationship may be between a person and their organization, a business process, a software/hardware tool or any other entity. It should be noted at this point that there are three important dimensions that characterize user models and have been identified as early as 1979 by Rich [1], namely:

- One model of a single canonical user vs. a collection of models of individual users.
- Models specified explicitly vs. models inferred by the system on the basis of user behavior.
- Long-term user models that represent demographics or general interests of users vs. short-term user models that are suitable for a specific session or task.

Moreover, according to one of the very first user model definitions, a user model is composed by information specific to each individual user, which describes specific user features [2]. Through the user model, the system may distinguish between different users and adapt itself to the particular user needs. In order to identify a meaningful way of describing the inherent uncertainty of the latter observation, we propose a *fuzzy* user model to deal with vagueness in users' needs and knowledge descriptions. Without such information deriving from the user model, all users would be treated equally [3]. A perfect user model would include all real-life features of users' behavior and knowledge that affect their performance and efficiency. However, because the construction of such complex model is typically considered to be a very difficult task, simplified models are used in practice. Keeping in mind the three aspects that have to be considered regarding a user model [4], namely: a) what type of information about the user is included in the model and how it is obtained, b) the representation of this information within the particular ecosystem, and c) the process of forming and updating the model, in the following we ‘ll attempt to tackle the first two of them.

The remaining of this paper is organized as follows: in Section 1 we provide a summary of related research works. In Section 2 we give a brief overview of the architectural framework of ‘‘Social&Smart’’ endorsed herein, whereas in Section 3 we discuss the users’ real-life perspective and how users may be modeled through a number of fuzzy user profiles. Finally the role of context and how it influences the overall process is discussed in Section 4, where our concluding remarks and ideas on future works are contained in Section 5.

1. Related works

Although, by definition the tasks of user and task modeling and analysis are not heavily related, it is not unusual for one modeling study to influence the other, especially during advanced iterative design cycles and usability analysis of systems that are being used. Within the exploited ‘‘Social&Smart’’ framework, both approaches will be considered during both its social network design and small scale mock-up phases for users and usage design approaches, respectively. In many cases, we are not interested in user modeling in a general sense, but only in user performance (task) and background knowledge with respect to tasks in a certain domain (context). In this case, an adequate user model may be restricted to a small set of user attributes related to a specific task. Kobsa revised generic user modeling systems in [5], in terms of their design approach and implementation into adaptive and personalized systems. This survey discusses approaches varying from definition of hierarchically ordered user stereotypes (e.g., ‘‘personas’’) and rules (using first order logic) for user model inferences to generalizing and extrapolating data collected from unobtrusive online user input.

Introduced by Cooper [6] early *personas* were rough sketches, but over time his method evolved to include interviews or ethnography to create more detailed characters. This initial methodology was extended and applied to popular operation systems and software such as MSN Explorer and Windows [7] or even EuropeanaConnect, a Best Practice Network funded by the European Commission [2]. A totally different approach attempts to model extreme characters, rather than users sharing common characteristics, considering radical personalities [8].

Furthermore, [9] discusses a number of challenges for machine learning that have hindered its application in user modeling and reviews approaches to resolving them, namely, the requirement for large and labeled data sets of high dimensionality as well as computational complexity restrictions for online applications and capability of adjusting to highly dynamic interaction environments, to name a few. World Wide Web and Social Networks are by definition such interaction environments. The usage modeling approach [10] attempts to tackle this aspect of user modeling. Whereas user-centered design makes users per se the center of attention and seeks to promote user satisfaction with the entire user experience, usage-centered design is more narrowly focused on user performance.

[2]EuropeanaConnect, `http://www.europeanaconnect.eu/`, last retrieved: April 2013

In usage-centered design the models are in the foreground with user studies and user involvement in the background.

With respect to the inherit contextual information available, authors of [11] reviewed an impressive 423 (out of 1419) articles related to context-aware approaches in literature and compiled a survey of the research area also proposing a classification framework. Their research also indicates the increasing amount of attention, corresponding to both its importance and dynamics, the area has received from the academic community. The authors concluded that most of the research performed in the area is focused on the Application and Concept layers, although Application and Interface layers tend to converge.

Most of the above context-aware systems focus on the external context, called physical context. External context means context data collected by physical sensors. It involves context data of the physical environment, location data, distance, function on to other objects, temperature, sound, air pressure, time, lighting levels surrounding users, and so on. However, a few authors have addressed utilizing the cognitive elements of a user's context. Various algorithms used in context-aware systems are classified into two parts. First, algorithm is utilized to infer high-level con-text of user. According to levels of abstraction, context is divided into low-level context and high-level context. Low-level context is raw data collected directly from physical sensors, while high-level context is inferred from low-level context. Although context awareness is important, context management and its integration is also crucial to achieving optimal user experience. There is no sense gathering and analyzing all the input representing the context without utilizing it appropriately. This can be accomplished by fusing the context and user modeling for personalized services and systems [12]. The authors study the integration and fusion of contextualization which complements personalization, based on user modeling, so that environmental states or the context of use can also be taken into account

In [13] authors propose an agent-based framework for providing the personalized services on context-aware computing, utilizing the extracted users' preferences and association rules. Data gathering layer collects and processes the users' profiles such as sex, age, job and hobby, the raw contexts (sensed data) such as time, location and temperature, and the selected services by the users such as destination. Context management layer infers the current high-level context processing the raw context and classifies the users' profile and services according to the reasoned high-level context using the filtering agent. Finally, in [14] the authors designed and developed ContextPhone, a software platform consisting of interconnected modules provided as a set of open source libraries for Symbian OS, residing between the application and device layer.

2. Basic ecosystem architecture

Within the framework of ''Social&Smart'', a *Networked Intelligence* module collects feedback from users regarding their satisfaction from recipes from one side, and responses from appliances themselves, on the other side, thus forming a permanent recipe optimization loop with offline advices and suggestions from the part of appliance manufacturers. In principle, the architecture of ''Social&Smart'' may be divided into three layers 1, namely: *lower*, *middle* and *top*. The lower layer is formed by all actual devices such as a fridge, a washing machine, a microwave oven etc., where each one is abstracted by what we call a Unified-Node (UN). The UN is the first level of device abstraction. Its role is to: i) uniquely identify a device, ii) represent the device in terms of its properties, and iii) constitute a bidirectional gateway for all communication between devices and middleware.

The middle layer is constituted by a set of modules, variously interconnected to interpret and control the commands issued by the users. To this aim, the latter must interface with any device found in the home, i.e. any UN representing an actual device. It must be capable both of managing and interfacing with devices gathered in logical clusters, such as all the devices located in a certain room, and of processing logical rules for adapting optimally the instructions to the devices specifications and limitations. The above modules will support these functionalities in two different modes, instantaneous commands, and recipe execution. The appliances' interface will be enhanced in terms of semantics via processing of recipes and rules by the knowledge base; the latter serves also as an intelligent conflict resolution mechanism that decides on future actions, thus resolving a conflict of resource/appliance allocation, which could lead to potential resource deadlocks. Recipes are transformed into explicit instructions to appliances, implementing a richer – compared to the one provided by the UN appliance abstraction – description for all domestic devices.

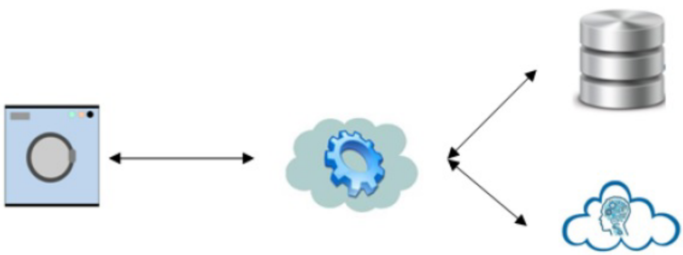

Figure 1. Abstract depiction of layers.

At the top layer, users interact with the middleware through a proper front-end either individually, e.g., a user sending recipes to his home, or through the users's community social network. From the ''Social&Smart'' point of view, a social network is a large database, i.e. the users' database, with an inquiry system based on advanced clustering algorithms. Exploiting this basis, one may build a series of services, such as automatic friend finding, proposal of interest groups, forums, etc.. The two elements that set apart the community social network are the way it fills the database and the main service it offers.

In principle, subscribing to a common social network, such as Facebook, requires to enter a series of personal data that form the user profile. Providing this information is in general optional for the user. The user may want to enrich his profile both to give other users means for discovering him as a friend and to increase his appeal (for instance by publishing interests, activities etc.). Quite on the contrary, a user registers into the ''Social&Smart'' community social network almost automatically. Once he contacts the social network he receives an ID and is roughly geo-localized. The same occurs in the case of a single appliance, thanks to smart appliance self-discovery facilities. To these basic data, additional ones may be optionally added, which mainly concern practical aspects of the homes, for example the floor plan indicating where the appliances are located (to rule the appliances noise) or the maximum power supplied by the electrical meter (to avoid overloads). Each time the user asks for a recipe, she/he enriches her/his profile; the same holds for user feedbacks. Of course, a recipe request must be entered by the user. But this is neither burdensome (because it is rewarded by the recipe), nor arbitrary (because only valuable and exact information needs to be entered). Finally, there is no need for strict personal identification of users. On the other hand, appliances must be completely identified through technical sheets supplied by their manufacturers (or every available documentation in the early implementations), as they constitute a part of the database which will be inquired during the creation of the recipes. Finally, typical social network services will be provided, initiating various forms of information exchanges such as friendship, files, forums etc. Of course, in such an environment, the main (possibly, sole) service provided to users will be recipe generation.

3. Fuzzy user models

Towards a rather simplified user model to be used in practice, an efficient user model representation formalism, such as ontologies ([15]), presents a number of advantages. In the context of the current work, ontologies are suitable for expressing user modeling semantics in a formal, machine-processable representation. As an ontology is considered to be ”a formal specification of a shared understanding of a domain”, this formal specification is usually carried out using a subclass hierarchy with relationships among classes, where one can define complex class descriptions (e.g. in Description Logics (DLs) [16] or Web Ontology Language (OWL) in [17]). Amongst all possible ways to describe ontologies, one may be formalized as:

$$O = \{C, \{r_{ab}\}\}, where\ r_{ab} : C \times C \to \{0,1\} \tag{1}$$

In equation (1), O is an ontology, a and b are two concepts (i.e., user models) belonging to the set C of concepts described by the ontology and r_{ab} is the semantic relation amongst these concepts. The proposed knowledge model is based on a set of concepts and semantic relations between them, that form the basic elements towards semantic interpretation of user models. Although almost any type of relation may be included to construct such knowledge representation, the two categories commonly used are taxonomic (i.e., ordering) and compatibility (i.e., symmetric) relations. However, as extensively discussed in the literature (e.g., in [17]), compatibility relations fail to assist in the determination of the context and the use of ordering relations is considered a necessity for context-aware user modeling tasks.

A last important point to consider when designing such a knowledge user model is the fact that real-life data often differ from research data. Real-life information is in principal governed by notions, such as *uncertainty* and *fuzziness*, thus its modeling should be based on *fuzzy* relations, as well. To tackle this observation and as a means to take into account the approximative nature and the inherent uncertainty involved in the interpretation of user needs and user wishes in a formal way, we propose the introduction of fuzzy representations, based on fuzzy theory ([18], [19]), as a formal grounding for the development of our user model. Thus, we propose a fuzzification of the previous ontology definition, as follows:

$$O_F = \{C, \{R_{ab}\}\}, where\ R_{ab} = F(r_{ab}) : C \times C \to [0,1] \quad (2)$$

In equation (2), O_F defines a fuzzified ontology, C is again the set of all possible concepts (i.e., user models) it describes and R_{ab} denotes a fuzzy semantic relation amongst the two concepts a and b. The latter depicts the fact, that, even when the meaning is clear, relations among real-life concepts are often a matter of degree, and one way to efficiently represent and model them is by the use of fuzzy relations.

Given a universe $\mathscr{V}$ of users $\mathscr{U}$, a crisp (i.e., non fuzzy) set S of concepts on $\mathscr{V}$ is described by a membership function $\mu_S : \mathscr{V} \to \{0,1\}$. The crisp set S may be defined as $S = \{s_i\}$, $i = 1,..,N$. A *fuzzy* set F on S may be described by a membership function $\mu_F : S \to [0,1]$. We may describe the fuzzy set F using the well-known sum notation for fuzzy sets [20] as:

$$F = \sum_i s_i/w_i = \{s_1/w_1, s_2/w_2, \ldots, s_n/w_n\} \quad (3)$$

where:

- $i \in N_n$, $n = |S|$ is the cardinality of the crisp set S,
- $w_i = \mu_F(s_i)$ or, more simply $w_i = F(s_i)$, is the membership degree of concept $s_i \in S$.

Consequently, equation (3) for a concept $s \in S$ may be transformed equivalently as:

$$F = \sum_{s \in S} s/\mu_F(s) = \sum_{s \in S} s/F(s) \quad (4)$$

Let now $\mathscr{R}$ be the crisp set of fuzzy relations defined as:

$$\mathscr{R} = \{R_i\}, R_i : S \times S \to [0,1], \quad i = 1,..,M \quad (5)$$

Then the proposed fuzzy ontology contains concepts and relations and may be formalized as follows:

$$\mathscr{O} = \{S, \mathscr{R}\} \quad (6)$$

In equation (6), $\mathscr{O}$ is a fuzzy ontology, S is the crisp set of concepts described by the ontology and $\mathscr{R}$ is the crisp set of fuzzy semantic relations amongst these concepts.

Given the set of all fuzzy sets on S, $\mathscr{F}_S$, then $F \in \mathscr{F}_S$. Let $\mathscr{U}$ be the set of all users $\widehat{u}$ in our framework, i.e. a user $\widehat{u} \in \mathscr{U}$. Let $\mathscr{P}$ be the set of all user meanings and $\mathscr{P}_{\mathscr{O}}$ be the set of all user meanings on $\mathscr{O}$. Then $\mathscr{P}_{\mathscr{O}} \subset \mathscr{F}_S$ and $\mathscr{P}_{\mathscr{O}} = \mathscr{F}_Z \subset \mathscr{F}_S$, whereas $P_{\widehat{u}} \in \mathscr{P}_{\mathscr{O}}$ depicts a specific user model.

3.1. Fuzzy semantic relations

At this point, where tolerance to imprecise descriptions is an assumed given, the relations between model concepts take on a key role in harnessing the degree of fuzziness involved in the discussed framework and help us handle this uncertainty. As a novel contribution, we propose an enhancement based on the exploitation of fuzzy ontological information as a source of semantic information and/or an aid to relate different parts of the user modeling process. The extra semantics (precise classification, explicit fuzzy relations between concepts) supply a rich source of additional knowledge, enabling significant improvements with respect to the results that can be achieved by the use of unrelated or crisp plain concepts. Under this interpretation, in order to define, extract and use both a set of concepts, we rely on the semantics of their fuzzy semantic relations. As discussed in the previous subsection, a *fuzzy binary relation* on S is defined as a function $R_i : S \times S \to [0,1], i = 1,..,M$. The inverse relation of relation $R_i(x,y)$, $x,y \in S$ is defined as $R_i^{-1}(x,y) = R_i(y,x)$. We use the prefix notation $R_i(x,y)$ for fuzzy relations, rather than the infix notation xR_iy, since the reader is considered to be more familiarized to the former. The *intersection*, *union* and sup-t *composition* of any two fuzzy relations R_1 and R_2 defined on the same set of concepts S are given by:

$$(R_1 \cap R_2)(x,y) = t(R_1(x,y), R_2(x,y)) \tag{7}$$

$$(R_1 \cup R_2)(x,y) = u(R_1(x,y), R_2(x,y)) \tag{8}$$

$$(R_1 \circ R_2)(x,y) = \sup_{w \in S} t(R_1(x,w), R_2(w,y)) \tag{9}$$

where t and u are a fuzzy t-norm and a fuzzy t-conorm, respectively. The standard t-norm and t-conorm are the *min* and *max* functions, respectively, but others may be used if appropriate. The operation of the union of fuzzy relations can be generalized to a number of M relations. If $R_1, R_2, ..., R_M$ are fuzzy relations in $S \times S$ then their union R^u is a relation defined in $S \times S$ such that for all $(x,y) \in S \times S$, $R^u(x,y) = u(R_i(x,y))$. A transitive closure of a relation R_i is the smallest transitive relation that contains the original relation and has the fewest possible members. In general, the closure of a relation is the smallest extension of the relation that has a certain specific property, such as the reflexivity, symmetry or transitivity, as the latter are defined in [19]. The sup-t transitive closure $Tr^t(R_i)$ of a fuzzy relation R_i is formally given by:

$$Tr^t(R_i) = \bigcup_{j=1}^{\infty} R_i^{(j)} \tag{10}$$

where $R_i^{(j)} = R_i \circ R_i^{(j-1)}$ and $R_i^{(1)} = R_i$. It is proved that if R_i is reflexive, then its transitive closure is given by $Tr^t(R_i) = R_i^{(n-1)}$, where $n = |S|$ [19].

Based on the relations R_i we first construct the following combined relation T, to be further utilized in the definition of context C:

$$T = Tr^t(\bigcup_i R_i^{p_i}), \quad p_i \in \{-1,0,1\}, \quad i = 1 \ldots M \tag{11}$$

where the value of p_i is determined by the semantics of each relation R_i used in the construction of T. More specifically:

- $p_i = 1$, if the semantics of R_i imply it should be considered as is,
- $p_i = -1$, if the semantics of R_i imply its inverse should be considered,
- $p_i = 0$, if the semantics of R_i do not allow its participation in the construction of the combined relation T.

The transitive closure in equation (11) is required in order for T to be taxonomic, as the union of transitive relations is not necessarily transitive, independently of the fuzzy t-conorm used. In the above context, a fuzzy semantic relation defines, for each element $s \in S$, the fuzzy set of its ancestors and its descendants. For instance, if our knowledge states that ”JFK assassination” is before ”Bosnia war” and ”Bosnia war” is before ”9/11 attack”, it is not certain that it also states that ”JFK assassination is before ”9/11 attack”. A transitive closure would correct this inconsistency. Similarly, by performing the respective closures on relations that correlate pair of concepts of the same set, we enforce their consistency.

For the purpose of analyzing textual descriptions, relation T has been generated with the use of a small set of fuzzy taxonomic relations, whose semantics are derived primarily both from the MPEG-7 standard and specific ‘‘Social&Smart’’ user requirements and are summarized in Table 1. This approach is ideal for the user modeling interpretation followed herein; when dealing with generic user information, focus is given on the semantics of high level abstract concepts.

Table 1. Fuzzy semantic relations used for generation of combined relation T.

Name	Inverse	Symbol	Meaning	Example	
				a	*b*
Specialization	Generalization	$Sp(a,b)$	b is a specialization of a	appliance	fridge
Part	PartOf	$P(a,b)$	b is a part of a	house	bathroom
Example	ExampleOf	$Ex(a,b)$	b is an example of a	fridge	Siemens
Instrument	InstrumentOf	$Ins(a,b)$	b is employed by a	clean	vacuum cleaner
Location	LocationOf	$Loc(a,b)$	b is the location of a	cooking	kitchen
Patient	PatientOf	$Pat(a,b)$	b undergoes the action of a	give	dust-buster
Property	PropertyOf	$Pr(a,b)$	b is a property of a	washing machine	rpm program

The aforementioned relations are traditionally defined as crisp relations. However, in this work we consider them to be fuzzy, where fuzziness has the following meaning: high values of $Sp(a,b)$, for instance, imply that the meaning of b approaches the meaning of a, while as $Sp(a,b)$ decreases, the meaning of b becomes narrower than the meaning of a. A similar meaning is given to fuzziness of the rest semantic relations of Table 1, as well. Based on the fuzzy roles and semantic interpretations of R_i, it is easy to see that aforementioned relation (11) combines them in a straightforward and meaningful way, utilizing inverse functionality where it is semantically appropriate:

$$T = Tr^t(Sp \cup P^{-1} \cup Ex \cup Ins \cup Loc^{-1} \cup Pat \cup Pr) \tag{12}$$

Relation T is of great importance, as it allows us to define, extract and use contextual aspects of a set of concepts. All relations used for its generation are partial taxonomic relations, thus abandoning properties like synonymity. Still, this does not entail that their union is also antisymmetric. Quite the contrary, T may vary from being a partial taxonomic to being an equivalence relation. This is an important observation, as true semantic relations also fit in this range (total symmetricity, as well as total antisymmetricity often have to be abandoned when modeling real-life relationships). Still, the taxonomic assumption and the semantics of the used individual relations, as well as our experiments, indicate that T is “almost” antisymmetric and we may refer to it as (“almost”) taxonomic. Relying on its semantics, one may define the context C of a single concept $s \in S$ as the set of its antecedents provided by relation T in the ontology. Considering the semantics of the T relation, it is easy to realize that when the concepts in a set are highly related to a common meaning, the context will have high degrees of membership for the concepts that represent this common meaning. Understanding the great importance of latter observation, we plan to further investigate and integrate such contextual aspects of user models in our future work.

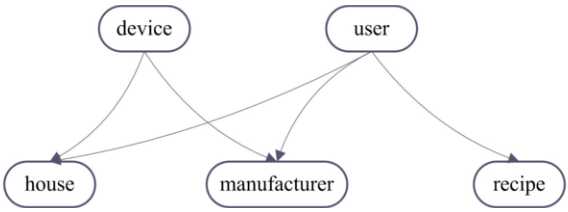

Figure 2. Concepts and relations example; concepts *device* and *user* are the antecedents of concepts *house* and *manufacturer* in relation T, whereas concept *user* is the only antecedent of concept *recipe*.

4. The role of context

The notion of context in our framework consists of a fuzzy region of an ontology, and is used to help focus or extend the ecosystem interpretation of user interests to a specific semantic area. In the profiling phase, which takes place off-line, the ecosystem detects user preference patterns by analyzing a large set of recorded user actions and requests. The ecosystem analyzes the semantic relations to find common thematic ground for different subsets of the usage history, e.g., in a clustering-based approach. The contextual notion implied here is taxonomic and of restrictive nature, and is used to reduce noise and uncertainty, by ignoring irrelevant user actions, and focusing on the most cohesive ones, from which it is safer to predict user interests. The context refers to whatever is semantically common among a set of elements, which may refer to the common meaning of a set of concepts, or to the overall topic of a document, respectively. When using an ontological knowledge representation, as the one proposed herein, to interpret the meaning of an information object, it is this type of context of a concept that provides its truly intended meaning. In other words, the true source of information is the semantic commonalities of certain concepts and not each one independently. The common meaning of concepts is thus used to best determine either their topics, or the associated user preferences to which they should be mapped.

Given the set of all fuzzy sets on S, $\mathscr{F}_S$, then $F \in \mathscr{F}_S$. Let $\mathscr{U}$ be the set of all users $\widehat{u}$ in our personalization framework, i.e. a user $\widehat{u} \in \mathscr{U}$. Let $\mathscr{P}$ be the set of all user preferences and $\mathscr{P}_\mathscr{O}$ be the set of all user preferences on $\mathscr{O}$. Then $\mathscr{P}_\mathscr{O} \subset \mathscr{F}_S$ and $\mathscr{P}_\mathscr{O} = \mathscr{F}_Z \subset \mathscr{F}_S$, whereas $P_{\widehat{u}} \in \mathscr{P}_\mathscr{O}$ depicts a specific user preference and is described as a fuzzy set. Since the fact that a user preference is relative to a user is clear, in the following we shall omit $_{\widehat{u}}$ as the index variable and use just P for short, as long as the meaning is clear.

Furthermore, let $\mathscr{C}_\mathscr{O}$ denote the set of all contexts on $\mathscr{O}$, $\mathscr{C}_\mathscr{O} \subseteq \mathscr{F}_S$. Let us also denote the crisp set of concepts characterizing the crisp (taxonomic) context as C, whereas its fuzzy counterpart C provides the context in the form of a fuzzy set of concepts on S, $C \in \mathscr{C}_\mathscr{O}$. As the last step, we define the contextualization of user preferences as a mapping $\Phi : \mathscr{P} \times \widehat{C} \to \mathscr{P}$ so that for all $p \in \mathscr{P}$ and $c \in \widehat{C}$, $p \models \Phi(p,c)$. In this context the entailment $p \models q$ means that any consequence that could be inferred from q could also be inferred from p. For instance, given a user $\widehat{u} \in \mathscr{U}$, if $P_{\widehat{u}} = q$ implies that $\widehat{u}$ "likes x" (whatever this means), then $\widehat{u}$ would also "like x" if his/her preference was p.

5. Conclusions and discussion

In this paper we attempted to discuss the ‘‘Social&Smart’’ paradigm of the pervasive Future Internet, as seen from the user-centered perspective. The research questions investigated were how users may be modeled through a number of fuzzy knowledge formalisms and how context may be modeled and integrated successfully in the process of, and especially within, the ‘‘Social&Smart’’ intelligent users/homes paradigm. In addition, this formal, machine-processable representation is used in order to define, extract and use both a set of concepts and their fuzzy semantic relations. We further plan to enhance and progress our research efforts on issues raised in Section 4: our scheduled future work includes incorporation of user and context information through a unified semantic representation, forming an adaptation mechanism that aims to provide real-life, intelligent personalized services and optimize the overall ‘‘Social&Smart’’ user experience.

Acknowledgments

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